Computational modeling interpretation underlying elevated risk-taking propensity in non-labor income

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Abstract: Individuals have been observed to show higher propensity to make risk investments using non-labor income compared to labor income, although the underlying mechanisms behind this phenomenon remain unclear. In this study, we proposed that non-labor income leads to a higher prior expectation of risky investment and a reduced sensitivity towards losses. To quantitatively test this hypothesis, we employed computational modeling. A total 103 participants were recruited and completed the Balloon Analogue Risk Task (BART) with an equal monetary endowment, either as a token for completion of survey questionnaires (labor income) or as a prize from a lucky draw game (non-labor income). We found that individuals endowed with non-labor income made more risky investments in the BART compared to those with labor income. To formally compare the differences in the dynamic risk investment process between individuals with different source of income, we built four candidate computational models (Bayesian Sequential Risk-taking Model, Target Model, Scaled Target Learning Model and Scaled Target Learning with Decay Model (STL-D)). Through computational modeling, we found that within STL-D, the optimal model, the non-labor income group preset a higher targeted number of pumps at the beginning, showed a lower learning rate towards loss trials where the balloon exploded, and had lower behavioral consistency. Our study suggests that the increased tendency for risky investments with non-labor income can be attributed to an increase in prior expectations on risk-taking and a diminished sensitivity towards loss. These findings provide potential intervention targets to mitigate irrational investments associated with non-labor income.

Key words: Non-labor income; Balloon Analogue Risk Task; Computational modeling; Hierarchical Bayesian analysis; Reinforcement learning

Public significance statements

Non-labor income such as windfall gains could also be pitfalls, since it might suddenly turn a money-grubber into a shopaholic. However, the underlying mechanisms of why individuals with non-labor income would have a higher propensity to make risk investments compared to those with labor income remain unclear. By reviewing existing literature and synthesizing prior research findings, we propose a dynamic and integrative framework suggesting that non-labor income might make people overly hopeful about risky investments and less worried about potential losses. By employing four candidate computational models, we quantitatively test this hypothesis. Our study implies that reducing excessively high risk-taking expectations as soon as one gets the money, and enhancing sensitivity towards loss outcomes in the midst of successive risky investments might be the key intervention targets to effectively prevent the tragic outcome from the extravagance of non-labor income in future.

And so I always say, "Yes, it's a million-pounder, as you see; but it never made but one purchase in its life, and then got the article for only about a tenth part of its value."

--- "The Million Pound Bank Note" (Mark Twain, 1893, p. 42)

Introduction

People usually receive non-labor income apart from labor income, ranging from lottery gains, stock market booms, inheritance, to gift coupons and so on. Despite anecdotes on lottery winners end up blowing all money by irrational splashes to hedonic or indulgent consumptions (e.g. gambling, etc.) (Arkes et al., 1994), people tend less likely to gamble with labor income for years of toil. And individuals tend to make more risky investments with unexpected gains than income from labor sources (Antonides & Ranyard, 2017; Henderson & Peterson, 1992; Zhang & Sussman, 2018). Studies also show that labor income (i.e. salary of the focal individual) is not a predictor of the frequency of gambling last year (Nyman et al., 2008), suggesting that labor income less likely leads to gambling as non-labor income does. Why non-labor income results in more risky investments remains a concern.

The mental account theory, the mainstream explanation to why non-labor income results in more risky investments, posits that individuals organize, store, evaluate and invest money differently from different sources (Arkes et al., 1994; Shefrin & Thaler, 2004). Non-labor income was put into windfall gains, whereas labor income was put into regular earnings. However, explanations on the exact difference in the pattern of organization and evaluation of money from labor versus non-labor sources are scarce, abstract and lack of empirical tests. The psychological implications

of non-labor income being put into the windfall gains mental account were only briefly discussed in previous studies, including discounted subjective values, less committed to and planning on how to spend, and so on (Arkes et al., 1994; Gajewski et al., 2022). How non-labor income dynamically and persistently elicits elevated risk preferences needs further theorization and corresponding empirical tests. Thaler and Johnson (1990)'s widely recognized theory, the House Money Effect, has received extensive empirical support in the field of risk investment (Bailey et al., 2023; Clark, 2002; Harrison, 2007). This theory provides valuable insights into how prior gains or losses experiences by investors can influence their reference point, at which investors psychologically distinguishes gains from losses. As a result, investors' sensitivity to losses is dynamically reduced, leading to a persistent inclination towards risky investments. Leveraging the House Money Effect, the current study aims to propose a dynamic and integrative framework on why non-labor income results in elevated risky investments, and then build computational models to quantitatively assess and directly test each component of the dynamic integrative framework.

In our integrative framework, we propose two key psychological processes that non-labor income would elicit: (1) an immediately increase in the propensity for risky investments upon receiving the income, which results from the elevation of the 'zero' reference point that psychologically distinguishes gains from losses, and (2) engagement in a dynamic cycle of risk-taking behavior with reduced sensitivity to losses during the investment process. Existing empirical evidence exclusively supports the first part of our framework (i.e. non-labor income enhances immediate risk-taking propensity), no empirical studies to date have investigated the second part of our framework, i.e. how non-labor income reduce loss sensitivity. A large number of empirical studies

consistently demonstrated a higher level of risky spending immediately after receiving non-labor income compared to labor income (Antonides & Ranyard, 2017; Thaler & Johnson, 1990; Zhang & Sussman, 2018). Existing studies have identified several key characteristics of non-labor income that contribute to the immediate increase in risk spending. These characteristics include a higher marginal propensity to consume (MPC), a tendency towards less planning, a discounted subjective value (Arkes et al., 1994), and the diversification of income sources (Gajewski et al., 2022). We thus hypothesize that individuals would have a higher propensity to make risky investments immediately upon receiving non-labor income.

The Quasi-Hedonic Editing Hypothesis (Thaler & Johnson, 1990) sheds insight on both the first and second part of our framework, i.e. how non-labor income immediately elevate risk-taking propensity and dynamically changes sensitivity to losses in the long run. According to this hypothesis, individuals would move their reference point to the gain domain upon endowed with an unexpected gain at the beginning of the investment, such that losses at the beginning were perceived no longer as net losses but a reduction of net gains (Kahneman & Tversky, 2013; Thaler & Johnson, 1990). The theory also speculates a key change in the perception towards gains and losses in the dynamic investment process. That is, they tend to integrate smaller losses with larger gains, in order to maximize overall happiness (Thaler & Johnson, 1990). This integration involves the cancellation of small loss in each trial, leading to a desensitization to losses in the dynamic investment process. The desensitization to losses, as predicted by the Quasi-Hedonic Editing Hypothesis, subsequently precludes individuals from reducing their investment levels after experiencing losses. As a result, risky investment are maintained at a persistently high level

despite the potential for losses. Building upon the Quasi-Hedonic Editing Hypothesis, we hypothesize that individuals engage in a dynamic cycle of risk-taking behavior with reduced sensitivity to losses during the investment process.

To test these hypotheses, we leverage the Balloon Analogue Risk Task (BART) to capture individuals' risk-taking propensities in dynamic risk decision-making (Lejuez et al., 2002) and incorporate the computational modeling approach to depict their dynamic risk decisions beyond analyzing traditional indices of risk-taking indicators. In this study, we incorporated well-established reinforcement learning (RL) models from previous studies as candidate models, including the Bayesian sequential risk-taking (BSR) (Pleskac, 2008), the Target model (Wallsten et al., 2005), the Scaled Target Learning (STL) model and its extension, the Scaled Target Learning with Decay (STL-D) (Zhou et al., 2021). We evaluated their model fit with behavioral data with a hierarchical Bayesian estimator. By intergroup-comparisons on key learning parameters, which depict risk-taking propensities at the beginning and sensitivity towards losses and gains, computational modeling enables a direct test on our theoretical model, i.e. how individuals with different mental accounts differ in their risk-taking propensity at the beginning and how they learn from negative versus positive investment outcomes.

In brief, in the current study, we investigate how income sources (i.e. the non-labor versus the labor income) influence individuals' dynamic risky decision-making process within the BART paradigm. We hypothesize that in dynamic risk-decisions, individuals with non-labor income showed persistent higher risk preference than those with labor income. Within a RL modeling

approach, we further hypothesize that individuals with non-labor income would preset a higher target number of pumps and have a decreased learning rate towards loss in BART, which might be the underlying reason of why they showed persistent higher risk preference.

Methods

Participants

We selected a target sample size of 51 per group to ensure adequate power to detect medium-sized effect (effect size *cohen's d* = .5, Type I error α = .05, power $1-\beta$ = .8) (Faul et al., 2007) based on a G*power calculation. However, in consideration of the exclusion of participants with potential emotional issues (e.g., depression or anxiety) and the success rate in the manipulation of mental account, we finally recruited 172 participants from local university by campus postings to ensure enough number of valid manipulations among participants free of emotional issues. Their age ranged from 17 to 26 (M_{age} = 20.92, SD_{age} = 1.86). All participants did not have reported history of mental disorders or substance use. This study was approved by the institutional review board of the Institute of Psychology, Chinese Academy of Sciences. All participants provided written informed consent.

Participants completed the Beck Depression Rating Scale (BDI), Patient Health Questionnaire-9 (PHQ-9) (Löwe et al., 2004), dimension of Neuroticism in NEO Personality Inventory (NEO-PI-N) (Costa Jr & McCrae, 2008), Trait Anxiety Inventory (TAI) (Spielberger et al., 1971), and the Barratt Impulsiveness Scale (BIS) (Patton et al., 1995) before the experiment to exclude outliers in personality measures. We also used the Positive and Negative Affect Schedule (PANAS) (Watson et al., 1988) to compare the arousal of positive emotion and negative emotion after the manipulation of mental account.

For our final sample who had completed all of the questionnaires, we first excluded (1) 3

participants who had moderate to severe depression indicated by BDI (BDI $\geqslant$ 19) or PHQ-9 (PHQ-9 $\geqslant$ 15), (2) 10 participants who were extreme outliers (i.e., BDI, PHQ-9, NEO-PI-N, TAI, PANAS or BIS scale scores exceed 3SDs), and (3) 8 participants whose risk-taking behavioral indicators in the BART exceeded mean + 3 SDs 151 participants were left after screening. 48 participants were excluded because they did not correctly distinguish endowment from different sources in the manipulation check (Most of them misclassified the money from lucky draw into labor Income). Eventually, 103 participants were included for analyses. Self-reported sources of endowment of these excluded participants could be found in the Supplementary Material Table S1.

Manipulation of Sources of Income

We manipulated the sources of income by randomly assigning participants into one of the two experimental conditions, i.e. the labor income condition and the non-labor income condition. Participants in the two groups received different cover stories about the sources of a same amount of endowment. For the labor income group, ¥15 of endowment was given to them immediately as a token for completing the questionnaire. For the non-labor income group, a gift was given as a token for completing the questionnaire as well. The aim of this step was to prevent their potential mental account of subsequent lucky prizes into labor income. Then, participants in the non-labor income group were invited to play a lucky draw game. They were told that in this game, they had a small chance (10%) to win a large prize (¥15) and a large chance (90%) to gain nothing. To facilitate the manipulation of a windfall gain, a confederate would draw together with the participant. Participants would see themselves win a large prize and the confederate win nothing. Upon hearing an announcement "Congratulations! You win ¥15!", participants would immediately

receive the money via Wechat or AliPay.

Immediately after receiving the money, participants were asked to complete the PANAS scale and were told that they could use the ¥15 as principal to compete the BART task. Participants were informed that they can win more money if play well, but can lose money if they play badly. They can also avoid the BART task by giving up pumping up any balloons. Participants first pumped two balloons for exercise before the formal experiment to familiarize with the task procedure. For manipulation check, participants were asked to report their perceived reason of why they get the ¥15, in which they could choose from “Labor income”, “Non-labor income” or “Other Reason but Not Listed in the Choices”. After the manipulation check, 10% of the amount of money obtained in BART was given as an additional bonus (Fig. 1.).

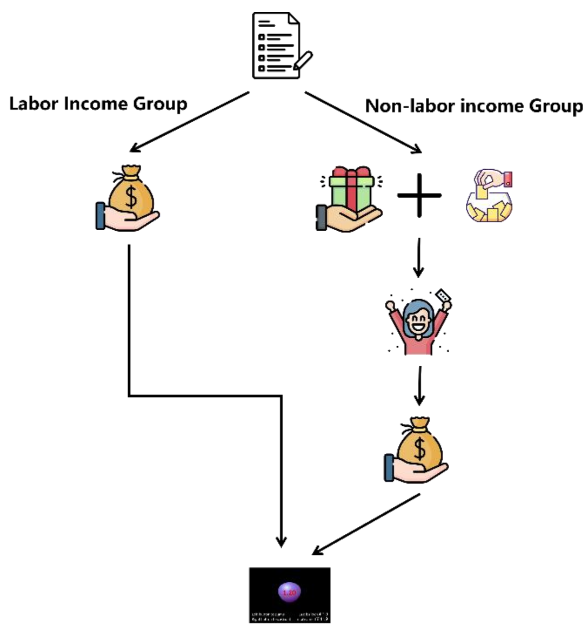

Fig. 1. Procedure. We manipulated participants’ mental accounts by stating the source of the same amount of ¥15 monetary endowment as (1) a token for completion of questionnaires (“labor income” condition) or (2) a prize from a lucky draw game (“non-labor income” condition).

Balloon Analogue Risk Task

We administered a 30-trial BART task adapted from Lejuez's study (Lejuez et al., 2002) . The task was programmed in E-prime 2.0. Participants were told that their goal was to earn as much money as possible. In each pump, participants had to choose between 'pumping' or 'stop pumping' by pressing one of two buttons (Fig. 2). If participants choose to pump, the balloon had a certain probability of explosion. If the balloon did not explode, ¥0.05 would be added to the temporary reserve. If the balloon exploded, participants would lose all the money from the temporary reserve. If participants stop pumping before the balloon explodes (they can even give up pumping at the beginning of any balloon to avoid potential loss). The next trial would start either after the balloon explodes or after participants stop pumping. A new balloon would appear on the screen and the temporary reserve would be reset to zero at the beginning of each trial. The maximal number of pumps allowed for each balloon was 128. The conditional probability of explosion after each pump if the prior pumps did not explode was equally set to 1/128. Thus, the probability of explosion would increase as the balloon got bigger, and the balloon would explode for certain after 128 pumps. At the end of 30 trials, participants would collect all the money from their permanent reserve as a part of their compensation.

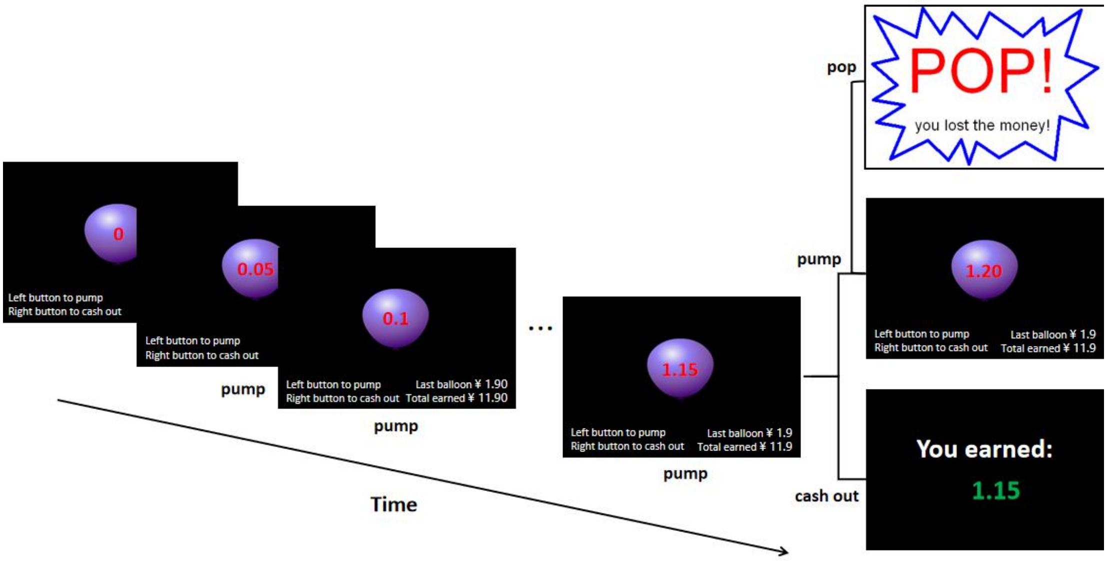

Fig. 2. Schematic of Balloon Analogue Risk Task.

Analytic Strategies

Beyond the manipulation check, we also used PANAS scale to indirectly verify the effectiveness of manipulation of mental account. We hypothesis that participants in the non-labor income group who won the lucky draw showed higher positive emotion than those in the labor income group. To test this hypothesis, we used independent sample t-tests to compare between-group differences in the positive emotion.

Further, to test the hypothesis that participants in the non-labor income group showed higher risk preference than those in the labor income group, we used independent sample t-tests to compare between-group differences in risk preference. Four behavioral indicators related to risk decision-making in BART were analyzed: (1) adjusted pumps, or the average number of pumps of win balloons (AP); (2) the number of pop-balloons (NP); (3) the average number of pumps of win-balloons immediately following a win (AP+); (4) the average number of pumps of

win-balloons immediately following a pop (AP-). To explore how the effect of explosion outcomes on the last balloon influenced the risk preference in the next balloon, we used a linear mixed model to investigate the main effects and interaction effects of the source of the money and feedback from the last trial on the number of pumps and earnings in each balloon. Learning was indicated by the main effect of feedback from the last trial on the number of pumps.

To formally compare the differences in the dynamic risk investment process between individuals with different mental accounts, we built four candidate computational models (Bayesian Sequential Risk-taking Model, Target Model, Scaled Target Learning Model and Scaled Target Learning with Decay Model) in Rstan (R version 4.1.3) (more details in Supplementary Material S2). Models were fit separately for participants with different mental accounts. Settings of prior distributions and ranges of estimated parameters were shown in Supplementary Material Table S3. Model comparisons were indicated by leave-one-out cross validation (LOO) information criteria, a common method to estimate out-of-sample predictive accuracy from Bayesian models (Vehtari et al., 2017). After selecting the optimal model, we used a hierarchical Bayesian approach to simultaneously acquire group and individual level parameter estimation with hierarchical Bayesian estimators in Rstan. We then performed between-group parameter comparison for different mental accounts using posterior distribution of different parameters within 89% highest density intervals (HDIs) (McElreath, 2020).

We also performed model recovery and parameter recovery to validate the robustness of parameter estimation in the optimal model (Supplementary Material S4-S5). For model recovery, we first

used the original parameter estimates for each individual to simulate their pumping process in each opportunity. We then calculated the Pearson correlation between the number of pumps in each opportunity in the original data and the simulated data to check if the simulated pump of each trial in BART could capture the key characteristic of participants' original responses. For parameter recovery, we first used individual-level parameter estimates to simulate the pumping process of each individual, and derived parameter estimates for each individual from the simulated data. Then we calculated the Pearson correlation between original and recovered parameter estimates across different participants. We repeated the above procedure for 20 times to derive the mean (SD) Pearson correlation indices for each parameter to evaluate the stability of parameter estimation.

Results

Data from 103 participants (M_{age} = 21.02, SD_{age} = 1.91) were included in the analysis. There were no significant between-group difference in demographics or personality measurements between the labor income group and the non-labor income group (Table 1). Independent sample t-tests suggested that participants in non-labor income group showed higher positive emotion than those in the labor income group ($t(101)$= 2.36, 95% CI = [1.05, 12.11], p < .05) while there was no significant difference in the negative emotion between the two groups ($t(101)$= 0.57, 95% CI = [-3.86, 6.97], p = .57).

Table 1 Group Differences in the Demographic Variables ($M \pm SD$).

Measure	labor income (N=57)	non-labor income (N=46)	Group difference statistics
Gender (%female)	59.65%	67.39%	Pearson chi-square(1) = 0.66, p = .418
Age (years)	20.88±1.92	21.20±1.92	$t(101)$= 0.84, p = .404
Year of College	3.26±1.48	3.33±1.54	Pearson chi-square(4) = 1.50, p = .827
BDI	3.51±3.34	3.04±2.96	$t(101)$= -0.74, p = .461
PHQ-9	4.65±2.97	4.74±3.14	$t(101)$= 0.15, p = .882
TAI	38.84±8.64	40.41±8.93	$t(101)$= 0.90, p = .368
NEO-PI-N	30.79±8.84	31.41±9.52	$t(101)$= 0.34, p = .732
BIS	62.11±7.47	64.83±8.85	$t(101)$= 1.69, p = .094

Note: BDI = Beck Depression Rating Scale; PHQ-9 = Patient Health Questionnaire-9; TAI = Trait Anxiety Inventory; NEO-PI-N = dimension of Neuroticism in NEO Personality Inventory; BIS = Barratt Impulsiveness Scale.

Independent sample t-tests suggested that individuals in non-labor income showed higher risk preference convergently across four behavioral indicators (Table 2): (1) adjusted pumps(AP): $t(101) = 3.43$, 95% $CI = [2.76, 10.33]$, $p < .001$, *Cohen's d* = 0.68; (2) number of pop-balloons(NP): $t(101) = 2.04$, 95% $CI = [0.03, 2.20]$, $p = .044$, *Cohen's d* = 0.41 ; (3) mean number of pumps of win-balloons immediately following a win (AP+): $t(101) = 3.47$, 95% $CI = [2.99, 10.95]$, $p < .001$, *Cohen's d* = 0.69; (4) mean number of pumps of win-balloons immediately following a pop (AP-): $t(99) = 3.60$, 95% $CI = [3.20, 11.04]$, $p < .001$, *Cohen's d* = 0.72.

Table 2 Group comparisons of BART indicators between labor income group and non-labor income group ($M \pm SD$).

BART indicators	labor income (N= 57)	non-labor income (N= 46)	Between-group comparison
AP	19.65 ± 8.25	26.20 ± 11.10	$t(101) = 3.43$, $p < .001^{***}$
NP	4.30 ± 2.40	5.41 ± 3.14	$t(101) = 2.04$, $p = .044^{*}$
AP+	20.28 ± 8.64	27.25 ± 11.73	$t(101) = 3.47$, $p < .001^{***}$
AP-	17.16 ± 8.51	24.29 ± 11.35	$t(99) = 3.60$, $p < .001^{***}$

$^{*}p < .05$; $^{***}p < .001$

To trial-by-trial explore how the manipulation of the source of income and feedback from last trial in BART would influence the current trial, we used a linear mixed model to examine the main and interactional effects of the source of income and feedback (i.e., the explosion outcomes of the last trial) on the number of pumps of the current trial. We found significant main effects of the source of income ($F(1,108) = 11.50$, 95% $CI = [-9.00, -2.41]$, $p < .001$) and feedback ($F(1,3001) = 23.20$, 95% $CI = [1.33, 3.16]$, $p < .001$), and none significant interaction between the source of income and feedback($F(1,3001) = 0.00$, 95% $CI = [-1.80, 1.85]$, $p = .981$). Post hoc test showed that the number of pumps of the current trial in the non-labor income group were significantly higher than the number of pumps of the current trial in the labor income group. The number of pumps of the current trial following a win were also significantly higher than the number of pumps of the current trial following a loss (Fig. 3.). In addition to reverifying the previous conclusion that participants in the non-labor income group showed higher risk-preference than participants in the labor income group, these results also implied that participants learn from past outcomes to adjust the number of pumps in the current trial based on outcomes from the last trial for both groups of participants.

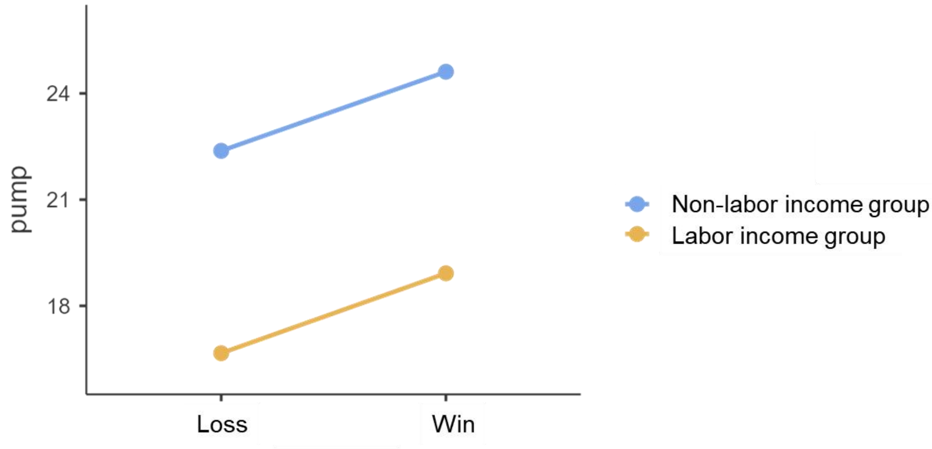

Fig. 3. The main effects of feedback from last trial on the number of pumps in the current trial.

Computational Modeling

Model comparisons of four candidate models (i.e. BSR, Target, STL and STL-D) between experimental conditions (i.e. labor income and non-labor income) were shown in Table **3**. For the labor income group, STL-D had the numerically smallest LOOIC. For the non-labor income group, BSR had the numerically smallest LOOIC, and had no significant difference with STL-D for goodness of fit by model comparisons (Mean Difference < SE). As STL-D captured the learning rate for winning and losing trials, which could reflect our interested psychological processes of how individuals learn from gains and losses underlying risk-taking behavior, we selected STL-D model as the optimal model for parameter comparison across conditions. Model recovery showed that the simulated data from the optimal model STL-D could capture key characteristics of the original data (Supplementary Material S4). Parameter recovery showed stable parameter estimation of STL-D, indicated by the high correlation between original and recovered parameters (Supplementary Material S5).

Table 3. Mean (SE) of LOOICs for different candidate models and model comparison results

group	Mean(SE) of LOOICs				Model comparison		
	BSR	Target	STL	STLD	BSR-STLD	Target-STLD	STL-STLD
labor income	7729.9 (213.0)	8135.3 (276.7)	7867.0 (209.0)	7719.0 (213.7)	5.5 (21.2)	208.2 (59.2)	74.0 (25.2)
non-labor income	6506.7 (162.3)	6749.6 (201.1)	6533.5 (161.8)	6515.3 (158.9)	-4.3 (22.9)	117.1 (43.9)	9.1 (14.7)

Descriptive statistics and 89% CI for the group-level estimation of each parameter is shown in Table 4 and Fig. 4. We found a credible between-group difference of learning rates in loss trial ($vloss$) (89% *HDI*: (0.03, 0.19)), target number of pumps before the first trial (ω_1) (89% *HDI*: (-0.11, -0.01)), and the inverse temperature (β) (89% *HDI*: (0.03, 0.24)) between labor income v.s. non-labor income condition. These results indicated that participants in the non-labor income group (1) preset a larger target number of pumps (ω_1) at the beginning of the game; (2) were less sensitive to feedback of losses ($vloss$); (3) acted more randomly, in which pump probability was less dependent on the target number of pumps (β).

Table 4. Parameter estimation and between-group comparison results (M±SD).

Parameters	Labor income	Non-labor income	Between-group 89% *HDI* (highest density intervals)

vwin	0.57±0.04	0.48±0.05	[-0.02, 0.19)
vloss	0.44±0.04	0.34±0.03	**[0.03, 0.19)**
ω_1	0.20±0.02	0.26±0.03	**[-0.11, -0.01)**
β	0.53±0.05	0.38±0.04	**[0.03, 0.24)**
α	0.11±0.02	0.18±0.04	[-0.13, 0.00)

Note*:* For BART used in our experiment, we set the maximal total number of pumps allowed in each trial is 128 (Lejuez et al., 2002), so the value of the target number of pumps (ω_k) is 1/128 of actual number of pumps, the value of ω_1 is between 0 and 1.

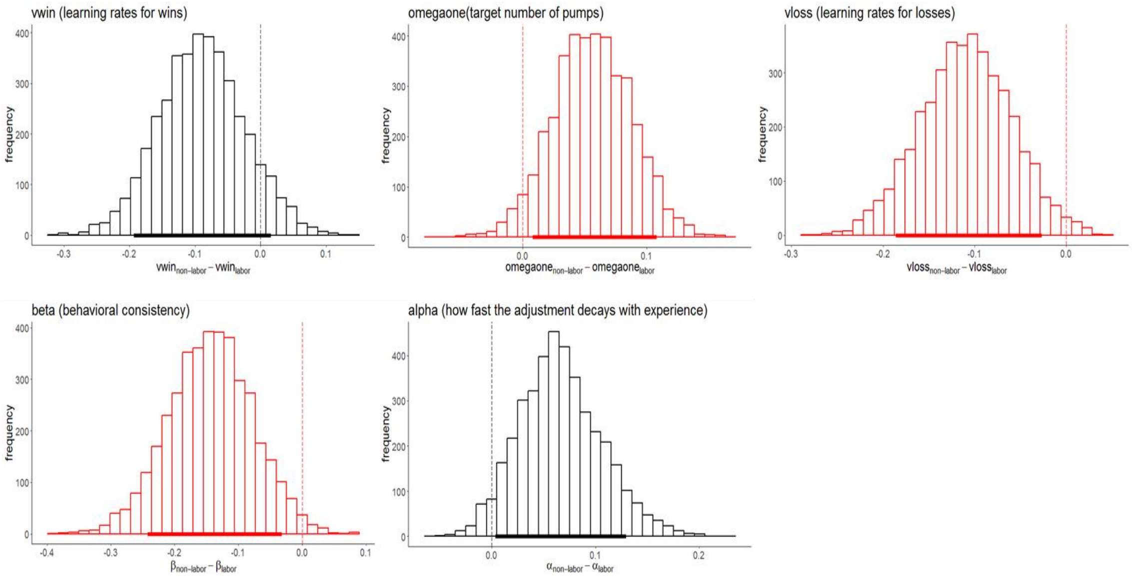

Fig. 4. Posterior distributions of differences of group mean parameters between individuals in non-labor income group and labor income group. The full thick black and red horizontal lines in figures indicates the 89% *HDI*. The black and red dotted vertical line indicates zero. Because the black line overlaps zero, there is no credible intergroup difference. Because the red line does not overlap zero, there is a credible intergroup difference.

Discussion

The current study proposed a dynamic and integrative framework to explain how the source of money affects subsequent dynamic risk decision-making process. Our framework highlighted that individuals with non-labor income would preset a higher number of risky investments at the beginning of this task, and would be desensitized towards losses. Model-free analyses showed that individuals have a higher risk preference in BART, and subsequent pumps were influenced by previous outcomes. To quantitatively examine the key components in our integrative framework, we employed a RL model. The findings from the RL model provide direct support for our hypotheses. Specifically, individuals with the non-labor income demonstrated a higher preset target for the number of pumps before the first trial (indicated by a higher ω_1), had a decreased learning rate to losses (indicated by a smaller $vloss$) and displayed more random decision-making (indicated by a smaller β) compared to individuals in labor income group. These results further validate the role of income source in shaping individuals' risk-related behaviors and offer a quantitative understanding of the underlying mechanisms for the elevated risk-taking propensity in non-labor income.

Our finding that individuals with non-labor income showed higher risk preference in dynamic risk decision-making and had higher target number of pumps (ω_1) were in line with our hypotheses and with existing studies in static decision-making (Arkes et al., 1994; Heilman et al., 2002). The higher values of ω_1 indicates that participants with non-labor income have more willingness to take risks than those with labor income even at the beginning of the BART. Previous consumption decision-making studies have also found that money in windfall gains account has an

irresponsibly higher marginal propensity to consume (Arkes et al., 1994; Kim & Tanford, 2021) than other account even before consumption. Finding from multi-period gambling also shows that individuals have the strongest willingness to take risks immediately after a large win, and such house money effect would weaken gradually over time (Hsu & Chow, 2013).

Moreover, computational modeling shows that the $vloss$ of participants in non-labor income group are significantly lower than that in labor income group. That is, individuals with non-labor income are less sensitive about the negative feedback in BART. This finding could be explained by the edition rule elicited by Quasi-Hedonic Editing Hypothesis (Thaler & Johnson, 1990). The reference point for participants in our labor income group is likely to be 0, whereas the reference point increases to 15 (i.e. the number of gain from the lucky draw) for the non-labor income group, representing a large gain at the beginning. To maximize happiness, the non-labor income group are less likely to exhibit loss aversion because losses fewer than 15 are no longer 'losses' in their mind in the process of integration with larger gains, this results in a desensitization to losses. Until the winnings are completely depleted, losses are cancelled out (Strahilevitz & Loewenstein, 1998; Thaler & Johnson, 1990). The increased target number of pumps (ω) and desensitization towards losses ($vloss$) found in our experimental study provide clear supports for the Quasi-Hedonic Editing Hypothesis. Further, the desensitization towards losses retains subsequent risk-taking at a continuously high level.

Moreover, we additionally found that participants in the non-labor income group base their actions less on the target number of pumps and more at random, and consequently has less rationality in

decisions, indicated by their lower behavioral consistency parameter β. Further, because the target number of pumps are primarily based on learning from the previous trial, the β can also be interpreted as segregation of outcome between trials (Barkan et al., 2005; Wallsten et al., 2005). In other word, participants with lower β values will base their actions less on the target number of pumps they had in mind but the outcome of a particular trial.

Our study has both theoretical and practical implications. In theory setting, despite incorporating existing theoretical perspectives to propose a dynamic and integrative framework on why non-labor income results in more risky investments, we went a step further from previous studies to directly uncover that non-labor income lead to a higher prior expectation of risky investment and a desensitization towards losses, which might be the key driver underlying individuals' continuous risk-taking behaviors. Our study also shed important lights to gambling studies. The tendency of desensitization towards both gains and losses for a windfall account is also typical for individuals with gambling disorders (Beck et al., 2009; FitzGerald et al., 2009; Romanczuk-Seiferth et al., 2015). The similarity between individuals with non-labor income and individuals with gambling disorders may suggest that desensitization to losses, higher risk-taking expectation, and irrationality might be potential mechanisms to gambling addiction. This could be addressed in future studies. In practical setting, our study highlights that to help windfall winners avoid pitfalls, effective intervention could target at cooling down consumption or risky investment immediately upon individuals receiving the non-labor income, and ameliorating loss desensitization and enhancing investment rationality in the long term.

The present study has the following limitations. A key limitation of this study is that our experiment only involves undergraduate students. Considerable proportion of participants were excluded due to failure in the manipulation of mental account. This insusceptibility to manipulation may be due to certain sample characteristics, i.e. higher educational background (Lee & Soberon-Ferrer, 1997). Future studies could replicate our results using non-student samples to eliminate the influence of higher educational background on mental account manipulations, and also test the generalizability of our results.

Conclusion

The current study proposed an integrative framework and systematically uncovered the reason underlying why non-labor income leads to higher risky preferences. We found that non-labor income was associated with an immediately higher targeted level of risk investments at the beginning, a desensitization towards investment losses, and lower rationality. From getting a coupon to winning the lottery, receiving an extra fortune happens all the time. But unlike in Mark Twain's "The Million Pound Bank Note" story, non-labor income such as windfall gains could also be pitfalls, since it might suddenly turn a money-grubber into a shopaholic. To mitigate extravagance associated with non-labor income, reducing excessively high risk-taking expectations as soon as one gets the money, and enhancing sensitivity towards loss outcomes in the midst of successive risky investments might be the key intervention targets in future.

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Author Contribution

YH: conceptualization, methodology, software, validation, formal analysis, investigation, data curation, writing – original draft, visualization, project administration

YJ: conceptualization, methodology, software, validation, formal analysis, data curation, writing – review & editing, visualization

BH: conceptualization, methodology, software, validation, formal analysis, investigation, data curation, writing – review & editing, visualization

TF: conceptualization, methodology, software, validation, investigation, resources, writing – review & editing, supervision, project administration

YZ: conceptualization, methodology, software, validation, investigation, resources, writing – review & editing, supervision, project administration, funding acquisition

Data availability statement:

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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